Machine Learning-Based Multiclass Classification of Li-Ion Battery Degradation Stages

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***Abstract*—As the need for reliable energy storage increases, more and more advancements have been made in applying machine learning (ML) to predict battery degradation and enhance lithium performance. In this article, a data-driven multiclass classification framework is presented to predict battery health states and estimate remaining useful life (RUL). The dataset consists of various electrochemical parameters, such as charge and discharge current, voltage, temperature, cycle count, and state of health (SOH). The continuous RUL values are grouped into three distinct classifications for ease of interpretation and classification: low, medium, and high degradation. Grid search cross-validation is used to train and fine-tune several ML algorithms, such as RandomForest, XGBoost, and LightGBM, to see how well they can predict. A thorough EDA is conducted to ascertain the interrelations of various features and their impact on battery degradation. LightGBM was the best of all the models we tried. It got both speed and accuracy right. XGBoost was also good; it kept working well even when the battery got worse. So, with this framework, you can check the health of your battery accurately and have a real chance of staying ahead with smarter, data-driven maintenance for electric vehicles and renewable energy systems.**

***Index Terms*—Li-ion batteries, machine learning, LightGBM, XGBoost, predictive maintenance, battery health prediction, and remaining useful life.**

I. Introduction

Battery systems that are reliable and last a long time are more important than ever as the number of people who use electric cars and renewable energy sources is rapidly increasing [1]. In this respect, lithium-ion batteries are the most prominent ones due to their high energy storage capacity, stable performance, and long service life. Fig[1] shows the evaluation of a lithium-ion (Li-ion) battery by a machine learning system. The system is indifferent to the application of the batteries and evaluates them to find out the residual life [2]. In other words, the system can be used in power tools, cars, or smartphones. The model helps the users to have better battery management and keep away from the risk by predicting whether their battery has a short, medium, or long remaining life [3].

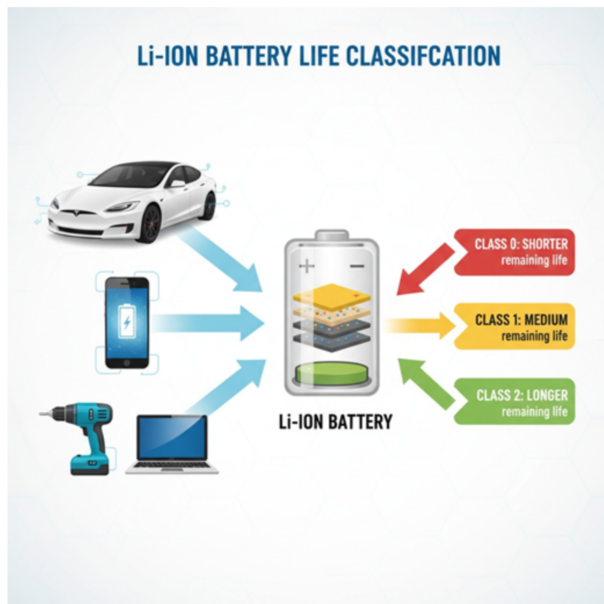

Fig. 1: ML-based Li-ion Battery Health Classification workflow

Bie, if batteries are to be kept running safely and you need To know what time you have to do maintenance, then a clear figure of their condition and how much their remaining life is. is indispensable. Certainly, some basic cleaning of data makes Models work better, but it still does not solve the problem. real - Li-ion batteries do not age linearly [4]. Their decay is complicated and unpredictable. Consequently, an An increasing number of researchers are switching to multiclass. machine learning [5]. This enables you to really identify the different stages of aging a battery goes through, instead of just giving a yes/no answer or a simple prediction. Most of the earlier studies stuck with binary classification or basic regression. The problem?, Those methods gloss over the slow, drawn-out changes that occur as a battery creeps from healthy to worn out. Here we went for something broader: we combined multiclass Classification with ensemble machine learning models — think Random Forest, XGBoost, and LightGBM — and threw in feature importance analysis to see what really matters [6] Instead of just tracking battery health, we broke down classifying the remaining useful life into the following categories: low, medium, and high degradation. That way the results will actually tell you something useful [7]. We also got our hands dirty with the data running deep ex- Perform exploratory analysis of data, EDA, to ascertain which electrochemical Actual factors that drive battery ageing. We have examined charge and discharge current, voltage, temperature, number of cycles, and state of health (SOH). By combining multi-class classification, straightforward interpretability tools, and sharp data insights; Our approach makes battery management systems both more: Smarter, more accurate, and easier to use, it's a real step forward for proactive maintenance [8].

II. CRITICAL SURVEY(RELATED WORK)

State of Health (SOH) and Remaining Useful Life (RUL) are two of the most common battery problems addressed by machine learning in battery prognostics. Regressing models such as Support Vector Regression (SVR) and Recurrent Neural Networks (RNNs) were used in the majority of initial articles. For example, Zhang et al. applied SVR to predict capacity loss of batteries just by voltage and temperature measurement. Simply using operational data, one can quite accurately detect degradation trends. The work of Seversons team was the next step in the use of RNNs, they made use of early cycles info to predict batteries lifetime [9]. They achieved a very high accuracy; however, their approach was computationally very expensive. The researchers gradually turned their focus to the issue of feature engineering. To address the challenge of prediction accuracy and to gain insight into internal battery processes, they committed themselves to the task of feature engineering [10]. Wang has demonstrated that the features extracted from the incremental capacity analysis (ICA) are highly correlated with the battery capacity loss. Richardsons work provided evidence that by fusing different health-indicators, such as internal resistance, charge capacity, and temperature, one can achieve more accurate predictions regardless of the manner in which the battery is utilized [11]. The Lius team came to the conclusion that Random Forest is a good fit for the prediction of the time a battery will be out of power, and at the same time, XGBoost and LightGBM not only train more quickly but also get better results when tested with different conditions, i.e., they are more stable. However, the majority of papers have a limitation in that they only focus on binary classification or regression.To resolve that issue, a multiclass system was made by us which distinguishes the decay at low, medium, and high levels [12].

Table[1] lays out a clear snapshot of what's already been done in battery health prediction .

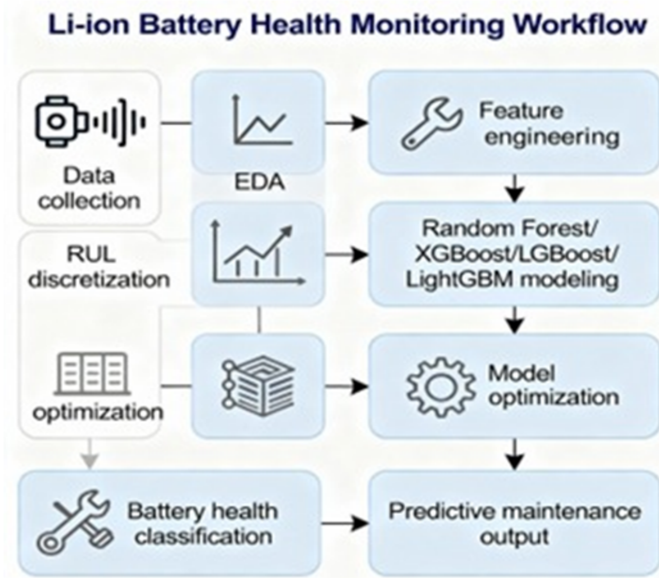

Fig. 2: Workflow of the System

Estimation of Remaining Useful Life (RUL): This study covers a lot of ground - NASA's battery logs, EIS data, and all kinds of complex sensor data. The researchers have tried various kinds of machine-learning algorithms - SVR, RNNs, ICA-based features, ensemble methods, you name it. Most of these articles show good results when estimating capacity fade, predicting battery cycles, identifying anomalies, or classifying health into various categories [13]. When looking at this body of work, you appreciate its contribution to supporting the notion of data-driven predictions, and that sequential modeling can be effective for this kind of project is a huge benefit, even if these articles allow good baseline comparisons. More importantly in this case, many of these articles resonate with the mission of this study - especially those associated with feature engines, mixing parameters, and classifying batteries into three health states. All in all, much of this research provides a foundation on which to develop this project.

III. METHODOLOGY

This is how we went about the multiclass classification for battery health states and determining the Remaining Useful Life (RUL). In Fig. 1, we show the complete process which started with data collection followed by data cleaning, feature selection, model building, and validation process. The entire Li-ion battery health monitoring pipeline is illustrated in Fig.[2]. It starts with data collection in raw form and some initial exploratory analysis. Next, we enter the feature engineering stage and get RUL sorted into easy classifications [14]. Then the model training occurs with applications of a Random Forest, XGBoost, and LightGBM based models. After evaluation and tuning of the final models, then the model can classify battery health with clear forecasted maintenance outcomes.

TABLE I: Summary of the Literature Review

Ref.	Dataset	Methodology	Outcome	Relevance to the Research
[1]	NASA Battery dataset	SVR for capacity fade estimation	Feasibility of using operational data	Supports data-driven degradation prediction
[2]	NASA Battery dataset	RNN for cycle prediction	High lifetime prediction accuracy	Validates sequence modeling for cycle-based data
[3]	Voltage/Temperature profiles	ICA Feature engineering	Improved degradation correlation	Aligns with feature engineering in our project
[4]	Multiple health indicators	Fusion of resistance + charge capacity	Improved robustness across conditions	Supports multi-parameter modeling
[5]	Li-ion cell datasets	Binary classifier (faulty/healthy)	High anomaly detection accuracy	Motivates multiclass extension used by us
[6]	EIS data	Three-class SVM health classifier	Categorises aging/intermediate/critical states	Directly aligned with our 3-class degradation modelling
[7]	High dimensional sensor data	Random Forest ensemble	Handles feature interactions well	Baseline model tested in our framework

A. Dataset Description

Prediction that was obtained from real-world experimental conditions in which batteries were charged and discharged in a controlled cycle [15]. The dataset captures how lithium-ion batteries degrade over time, reflective of the decays observed in electric vehicles and IoT devices, and consists of 680 entries. Each entry contains ten input features that signify the input characteristics that predict battery performance and a target variable, all of which were associated with significant electrical and thermal measurements for distinct, testing batteries. The key features used in this study are described below:

- **Battery ID:** A unique identifier for each battery cell tested.
- **Cycle:** The number of charge–discharge cycles, where a higher cycle count indicates greater usage.
- **ChI:** Charging current .
- **ChV:** Charging voltage.
- **ChT:** Charging temperature (°C).
- **DisI:** Discharging current .
- **DisV:** Discharging voltage .
- **DisT:** Discharging temperature (°C).
- **BCt:** Battery capacity trend indicator.
- **SOH:** State of Health.
- **RUL:** Remaining Useful Life .

B. Data Preprocessing and Feature Engineering

1) Data Cleaning and Normalization

It was noted that 2% of the dataset had missing values drawn from real value responses. The gaps were handled with the k-nearest neighbors, when k=5, to estimate and replace the missing observations.

2) RUL Discretization and Label Encoding

Continuous RUL values were discretized into three interpretable degradation classes to support multiclass classification:

- **Class 0 (Low Degradation)**
- **Class 1 (Medium Degradation)**
- **Class 2 (High Degradation)**

This discretization enhances interpretability for maintenance decision-making while preserving prognostic accuracy.

3) Feature Engineering

To characterize battery degradation more effectively, additional features were derived:

- **Capacity Fade Rate**
- **Internal Resistance Estimate**
- **Temperature Gradient**
- **Coulombic Efficiency**

C. Exploratory Data Analysis (EDA)

The exploratory data analysis (EDA) was extensive in analyzing feature distributions, degradation behavior, and feature dependencies. Pearson correlation coefficients helped identify and quantify linear relationships. The plots presented in Fig [3] shows how six significant battery parameters—current, voltage, and temperature, for example—change during charge and discharge. Each plot includes a histogram and a smooth curve, with the combination showing where most of the data points are located. Most of the distributions resemble a normal bell curve which indicates that the measurements are consistent and reliable regardless of the battery condition [16].

D. Machine Learning Models

Three advanced ensemble learning models were used for multiclass degradation state classification:

1) Random Forest (RF)

A bootstrap-aggregated ensemble of decision trees . Final prediction is obtained via majority voting:

2) XGBoost

A gradient boosting framework using second-order optimization and regularization , defined by:

3) LightGBM

A high-efficiency gradient boosting algorithm leveraging histogram-based computation and leaf-wise tree growth .

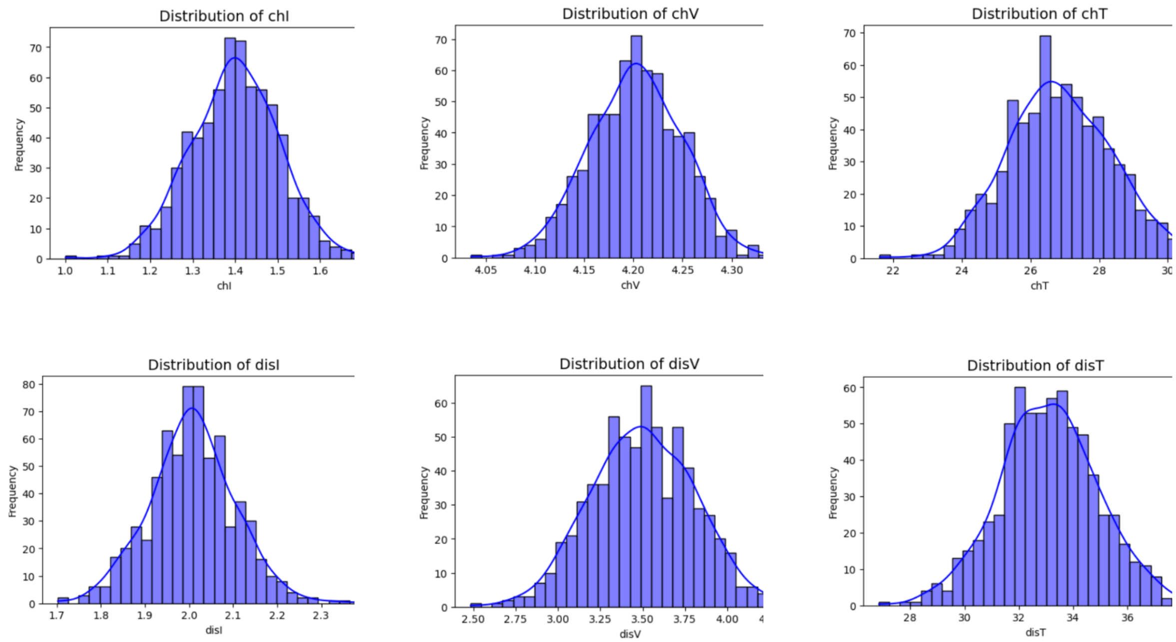

Fig. 3: Distributions of features

It offers superior training speed and scalability for large datasets.

E. Model Training and Hyperparameter Optimization

Stratified 5-fold cross-validation was used to preserve class proportions. Hyperparameter tuning was conducted using Grid Search:

- **Random Forest:** n_estimators [100, 200, 500], max_depth [5, 10, 15], min_samples_split [2, 5, 10]
- **XGBoost:** learning_rate [0.01, 0.1, 0.2], max_depth [3, 6, 9], n_estimators [100, 200, 500]
- **LightGBM:** num_leaves [31, 63, 127], learning_rate [0.01, 0.1, 0.2], n_estimators [100, 200, 500]

F. Performance Metrics

Performance metrics for the models were evaluated based on the standard classification metrics:

- **Accuracy , Precision , Recall , F1-Score**

IV. RESULTS AND DISCUSSION

At this point, we explore the experimental results, compare the models, and emphasize important findings from implementing this multiclass battery health classification framework. This isn't simply a catalog of metrics [17]. The real question is what models work well with respect to the why behind those differences, and how the details in the data sway them. Examining the accuracy simply, the precision–recall scores, as well as the confusion matrices all highlight which RUL classes basically never get confused, and which are more frequently confused with one another; the reason in most cases was due to similarities in their degradation paths [18].

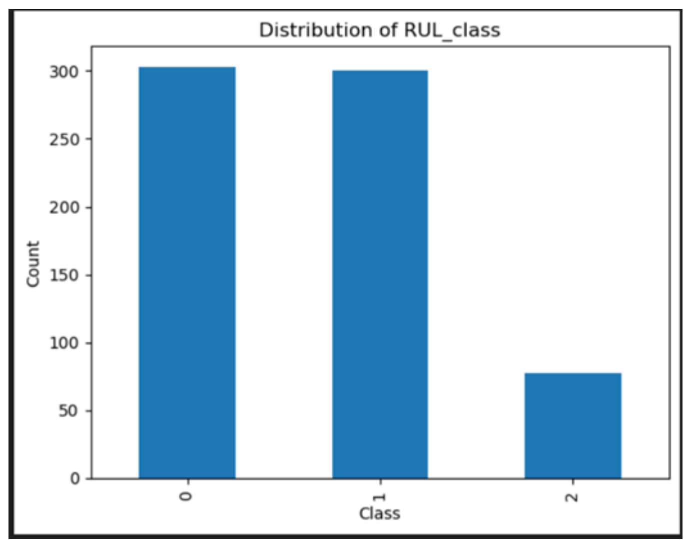

Fig. 4: Distribution of RUL_class

You can definitely see how preprocessing techniques such as such as normalization, feature filtering, and class balance. render the predictions of diverse models more concordant. All of this leads to clearer interpretations, growing our understanding of how model behaviors translate to battery in practical contexts. Fig. [4] Describes The bar graph depicts the distribution of classes by converting continuous RUL values into 3 classes.

The representations of class 0 and 1 have more members. than class 2, indicating a small class balancing problem.

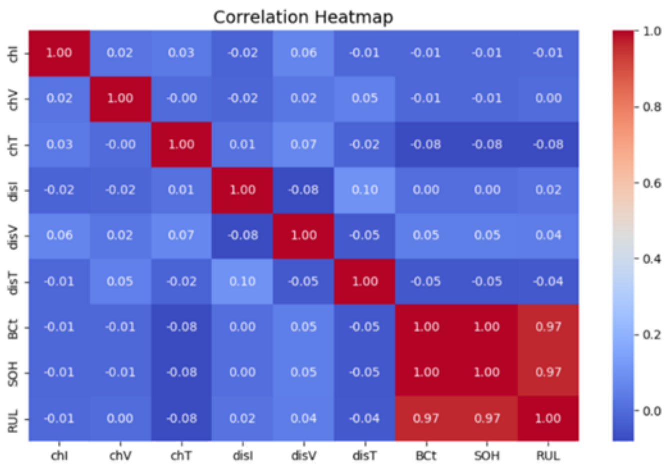

Fig. 5: Correlation Heatmap

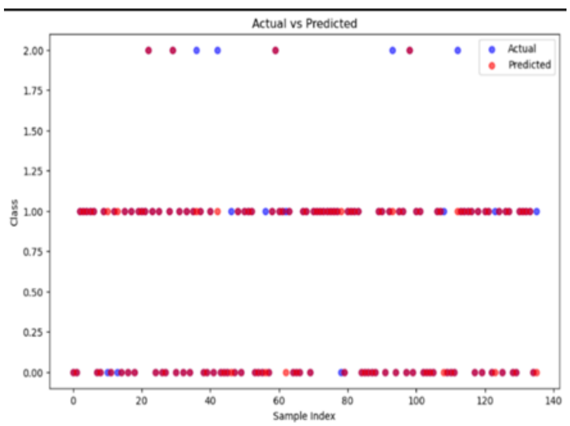

Fig. 6: Predicted vs Actual Class Comparison Plot

Fig[5] The correlation heatmap shows how key electrochemical features are connected. Battery capacity (BCt), state-of-health (SOH), and remaining useful life (RUL) are connected, suggesting a strong relationship among these three features. Most of the other features have negligible interaction with each other.

Fig[6] This plot shows the actual vs. predicted battery health classes for each test sample. The tightness between the points signifies that it has highly consistent and accurate class predictions.

A. *Exploratory Data Analysis Findings*

1) *Feature Correlation Analysis*

The results illustrate the intersection of electrochemical characteristics and battery degradation (see Fig. 4). Here are some other notes:

- **Cycle Count as a Key Indicator:** Cycle count exhibited a strong inverse relationship with SOH, underscoring its demonstrated accuracy as a leading indicator of battery deterioration and degradation.
- **Impact of Temperature:**Higher operating temperatures significantly increased the rate at which the battery lost capacity; in other words, if the battery is running hotter it is under more thermal stress, which sped battery degradation process and reduced lifespan.
- **Voltage Profile Degradation:** The stability of the voltage curve during the constant-current charging gradually weakened from the observation when the battery was repeatedly cycled. At higher cycle numbers, the change in the voltage profile with aging of the battery was clearly visible and the authors could even quantify the shift of the voltage profile with time [19].

2) *Class Distribution Analysis*

The RUL classes showed about 42% of samples in class 0, i.e., low degradation status. Class 1 or medium degradation class contained approximately 36%. Only about 22% of the samples were in class 2 or high degradation. [20]. Admittedly not a perfect balance; however, most batteries will not hit the critical states based on a common use case scenario.

B. *Model Performance Evaluation*

1) *Comparative Classification Performance*

We utilized 5-fold cross-validation to evaluate all the models and adjusted the hyperparameters fairly. The results speak for themselves: ensemble methods perform exceedingly well in capturing those nonlinear degradation patterns [21]. LightGBM had the overall highest accuracy in the multiclass tests. XGBoost also performed well and consistently, not moving in accuracy across the folds. Random Forest did not have the same accuracy, but it provided reliable and trustworthy predictions and was a good baseline [22]. In conclusion, gradient boosting methods handle complex battery health modeling better than anything else we explored.

TABLE II: Model Performance on Binary and Multiclass Classification

Model	Binary Classification	Multiclass Classification
RandomForest Classifier	100%	88.97%
XGBoost Classifier	100%	90.44%
LightGBM Classifier	95.5%	90.44%

Table [2] shows the effectiveness of the three ensemble learning models in classifying the state of health of a battery into two classes and into three classes. For a binary classification problem, the results obtained from these models are outstanding: 100% for Random Forest and XGBoost, and 95.5% for LightGBM.

However, with the introduction of a third class at different levels of degradation, that becomes very hard, as shown by [23]. The accuracies of all models have come down. LightGBM and XGBoost were able to maintain their maximum at 90.44%, while Random Forest managed only 88.97%, thus conceding its leading position.

Therefore, the models can successfully distinguish between healthy and degraded batteries, while the prediction of the correct level of degradation remains a challenging task. However, XGBoost and LightGBM are better at that than Random Forest.

V. Conclusion

The project studies machine learning to classify batteries based on health into three simple categories of low, medium, It is well-known for its difficulty due to dimensionality challenges and high degradation. This work investigates the generation of robust ensemble models using Combined with deep feature analysis, it also provides a complete overview of Li-ion battery aging. You get solid evidence based on reliable interpretation. The accuracy the level is 90.44%, quite impressive for predictive maintenance. in real life. Early warning signs are detected, safety is Improved and informed decision-making concerning energy storage. can thus be achieved. Due to its accuracy, speed, and its output results which are actually interpretable, this activity is directionally in searching for an improved battery. management in the future. Three important aspects have it brought a major impact, making this work stand apart from others. First, we presented a new way to split continuous RUL. into three simple categories: low, medium, and high. This makes battery management in real world applications much easier. Second, we really put the top ensemble models to the test and proved their effectiveness in navigating the complex patterns of electrochemical degradation. Finally, We conducted a solid feature importance review to do research on the aspects which are actually responsible for how the battery degrades, further processing into data.

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